

Answer Report on ‘Optimizing Electricity Procurement for Environmental and Economic Sustainability: A Predictive and Multi-Objective Approach for Year 2018’.



International Student Competition

Organised by: SustAInify '24, Sustainability Cell, IIT Bombay

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1 Time Series Forecasting

1.1 Objective:

The goal of this project is to forecast energy prices using historical data. Specifically, we aim to predict energy prices based on various features such as time of day, day of the week, month, and lagged prices.

1.2 Dataset:

The dataset used in this project consists of historical energy prices from year 2010 to 2017. It includes features such as timestamp and energy prices.

1.3 Modelling Approach:

We utilized a time series forecasting approach using the XGBoost (Extreme Gradient Boosting) algorithm. XGBoost is a powerful algorithm known for its efficiency and accuracy in handling structured/tabular data. The model was trained using the Timeseries Split cross-validation technique to ensure robustness in handling time-dependent data.

1.4 Feature Engineering:

Prior to modelling, we performed feature engineering to enrich the dataset with additional features that could potentially improve prediction accuracy. The features engineered include:

- Day of year
- Hour of the day
- Day of the week
- Quarter of the year
- Month
- Year
- Lagged prices (up to 3 lag periods)

1.5 Model Architecture:

The XGBoost model used in this project is configured as follows:

- Base Score: 0.5
- Booster: gbtrees
- Number of Estimators: 1000
- Early Stopping Rounds: 50
- Objective: reg:linear
- Maximum Depth: 5
- Learning Rate: 0.01

1.6 Evaluation:

1.6.1 R-squared Score (R²):

The R-squared score measures the proportion of the variance in the dependent variable (target) that is explained by the independent variables (features). The R² score ranges from $-\infty$ to 1, where a value closer to 1 indicates a better fit of the model to the data. In this evaluation, the R² score was calculated as -0.694.

1.6.2 Adjusted R-squared Score:

The Adjusted R-squared score is a modified version of the R-squared score that adjusts for the number of predictors (features) in the model. It penalizes the addition of unnecessary predictors that do not improve the model's explanatory power. The Adjusted R-squared score ranges from $-\infty$ to 1, with higher values indicating a better fit. In this evaluation, the Adjusted R-squared score was calculated as -0.696.

1.6.3 Interpretation:

The negative values of both R-squared and Adjusted R-squared indicate that the model performs worse than a model that simply predicts the mean of the target variable. This suggests that the model does not explain much of the variance in the target variable and may not be a good fit for the data.

1.6.4 Conclusion:

Based on the R-squared and Adjusted R-squared scores, it can be concluded that the model lacks predictive power and fails to adequately explain the variability in the target variable. Further investigation is recommended to identify potential issues with the model, such as overfitting, underfitting, or incorrect feature selection, and to improve its performance. Additionally, alternative modelling techniques may be explored to better capture the underlying patterns in the data and improve predictive accuracy.

2 Optimization

2.1 Objective of the Problem

The goal of this study is to optimize the procurement of electricity for a given demand of 1200 MWh/day, minimizing both cost and carbon footprint considerations. The objective of this part of the problem is to optimize the electricity procurement costs along with its environmental impact (in terms of Carbon Footprint) while ensuring a minimum of 20% renewable electricity utilization in its energy mix and report the following optimized quantities for the plant. The optimization focused on determining the optimal mix of electricity drawn from three given sources namely, the state electricity grid, a power exchange, alongside a fixed contribution from a captive solar power plant.

2.2 Methodology

The optimization problem is modelled using the Pymoo library, leveraging the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for multi-objective optimization. The decision variables included the quantities of electricity procured from the state electricity grid and through power exchange. The objective is to minimize both the total cost and the carbon footprint associated with the electricity procured. Constraints included meeting the total daily electricity demand and ensuring a minimum percentage of electricity came from renewable sources.

2.3 Problem Formulation

2.3.1 Fixed Parameters

- The proportion of Renewable Electricity out of the Total provided by the **Electricity Grid is 15%**
- The proportion of Renewable Electricity out of the Total provided by **Power Exchange is 5%.**
- Electricity provided by the company's captive solar power plant is **150 MWh/Day**
- The cost of electricity drawn from the company's captive solar power plant is **0 EUR**
- The price of electricity drawn from the State Electricity Grid is **57.62 EUR/MWh**

2.3.2 Decision Variables:

- *Quant_grid*: Quantity of electricity procured from the state grid
- *Quant_exchange*: Power exchange

2.3.3 Objectives:

- Minimize the total cost (sum of costs from grid and exchange for a year).

$$Total\ Cost = \sum(Quant_{grid} \times 57.62) + \sum(Quant_{exchange} \times exchange_cost)$$

- Minimize the total carbon footprint (based on the carbon intensity of the grid and exchange electricity for a year).

$$\text{Total Carbon Footprint} = \sum((0.85 \times \text{Quant}_{\text{grid}}) + (0.95 \times \text{Quant}_{\text{exchange}})) \times 0.95$$

Note: [1 MWh of Non-Renewable Energy generated using coal contributes to 0.95 MTCO₂e]

2.3.4 Constraints:

- Total electricity demand must be met.

$$\text{Quant}_{\text{grid}} + \text{Quant}_{\text{exchange}} + 150 \frac{\text{MWh}}{\text{day}} (\text{captive solar power}) = 1200 \text{ MWh/day}$$

- A minimum percentage of total electricity must come from renewable sources.

$$(0.15 \times \text{Quant}_{\text{grid}}) + (0.05 \times \text{Quant}_{\text{exchange}}) \geq 0.20 \times 1200 \text{ MWh/day}$$

2.4 Data

The exchange costs were derived from a dataset titled "Power Exchange Data_ 2018," derived from the predicted model explained above. Mapping of **dates** to **prices (EUR/MWh)** is done. The analysis is specifically conducted on **1st January 2018**, using the corresponding exchange cost from the dataset.

2.5 Results

The optimization process identified the quantities of electricity to be procured from each source that minimized the total cost and carbon footprint, subject to the given constraints.

2.5.1 Optimized Quantities on 1st January 2018:

- Optimised Percentage of the Total Renewable Electricity out of the Total Electricity: **20.43%**
- Optimised Quantity of Electricity to be drawn from the State Electricity Grid: **426.55 MWh**
- Optimised Quantity of Electricity to be drawn from the Power Exchange: **623.53 MWh**
- The total carbon footprint of the optimized electricity mix is **907.18 MTCO₂e**.

2.5.2 Visualization

A Pareto front graph is plotted (a reference to the Python file) to illustrate the trade-off between the total cost and carbon footprint of the optimized solutions. This visualization helps in understanding the feasible region of optimal solutions and the trade-offs involved.

2.6 Conclusion

The study successfully applies multi-objective optimization to the problem of electricity procurement from three different sources, minimizing cost and environmental impact. The NSGA-II algorithm facilitated the exploration of the trade-offs between these objectives, enabling decision-makers to select an optimal strategy that meets both economic and environmental goals.